

Spatial distribution and genesis of salt on the saline playa at Qehan Lake, Inner Mongolia, China

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ABSTRACT

Inland salt lakes and saline wetlands are intricate systems in which moisture and salinity are continuously changing and especially sensitive to climate change and human pressure. Remote sensing helps to monitor the dynamic changes in the moisture and salinity of salt lakes and saline wetlands. Based on the Landsat 8 satellite data, this paper developed a multivariable linear regression model (MLRM) to predict the spatial distribution of salt on the saline playa at the Qehan Lake in Inner Mongolia, China. The developed MLRM used the remote sensing spectral indices and the Tasseled Cap Transformation wetness band (TCTW) as a variable. By using the TCTW and the surface temperature inversion data, the response of salt to surface moisture and temperature in the dry lake bed was explored. The results showed: The MLRM with brightness index (BI) and the TCTW as the auxiliary variables has the nice applicability ($R_{adj}^2 = 0.598$, $RMSE = 1.640$). The MLRM established using the vegetation index NDVI may be more applicable to environments where vegetation and salts were doped-together. Salt distribution in the Qehan Lake may be controlled by flat lake bed and miniature piedmonts. There was a significant correlation between measured soil electrical conductivity (EC) and TCTW, but no correlation with surface temperature. The influence of surface temperature on salt may be biased towards the time scale.

1. Introduction

Saline playa is a ubiquitous natural landscape cell in arid and semi-arid inland areas. The main prerequisite for the formation of such a natural landscape is that evaporation exceeds rainfall. Capillary rise of the very shallow water table (0.01 to > 1.00 m, depending on distance from the lake) in these saline lake can lead to significant salt crust formation because of continuous supply of water and dissolved salts (Buck et al., 2011; Rosen, 1994b). As a kind of wetland, salt-affected natural landscapes are extremely sensitive to the changes in regional and global climatic conditions, soil physical and chemical characteristics, and hydro geological information (Kertész and Tóth, 1994). In salt lake or inland wetlands, soil salinity has been considered as a major factor controlling the distribution of vegetation, due to strong salt stress (He et al., 2011; Ji et al., 2009; Rogel et al., 2000). For example, salinization coerces the growth of wetland and their surrounding vegetation, and soil salinity directly impacts the productivity of the wetland ecosystem and its ecological environment. It also impedes the growth of vegetation to some extent (Glenn et al., 1999; Hamzeh et al., 2013; Periasamy and Shanmugam, 2017). In recent years, wetlands and lakes have been seriously threatened by climate change and excessive man-made disruption, or even dried up (Legesse et al., 2004; Mortsch, 1998;

Shafroth et al., 2002; Xi et al., 2017). Loss of water creates a fluffy soil structure that can be easily eroded by wind. Sandstorms often occur in these areas to cause environmental and ecological problems, such as desertification and grassland degradation (Cahill et al., 1996; Goudie and Middleton, 1992; He et al., 2011; Shao and Dong, 2006). For example, the increase in agricultural water use in the Aral Sea Basin has caused the lakes to dry quickly in recent years, and massive salt storm has formed (Micklin, 2007). Similarly, such as Owens Lake and Salton Sea in the United States, the Ebinur Lake in Xinjiang, China, and Mar Chiquita Lake in Argentina (Bucher et al., 2006; Bucher and Stein, 2016). Therefore, in planning ecological restoration projects for the disaster, first of all, it is necessary to have a sufficient understanding of the salinity distribution of the already dried lake or wetland in order to propose rationalization plans.

To elaborate detailed maps about the salinity distribution for large and medium-scale areas, a large number of soil samples are needed in the traditional way which makes mapping expensive and time consuming. Therefore, remote sensing technology appears to have advantages in this situation (Allbed and Kumar, 2013). Satellite image data and techniques have been successfully applied to monitor and map soil salinity. Multispectral data such as Landsat, SPOT, IKONOS, MODIS and QuickBird series of satellites have been found to be useful in

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estimating soil salinity used to notarize the spectral indices (e.g., vegetation index) that impact on salinization. They then developed a linear unmixing model to estimate soil salinization in semi-arid regions (Dehni and Lounis, 2012; Dwivedi et al., 2008; M et al., 2011; Meng et al., 2016; Periasamy and Shanmugam, 2017; Setia et al., 2013; Teggi et al., 2012). The multispectral images of Landsat 8 OLI (Operational Land Image) are also used for quantitative inversion of soil salinization (Meng et al., 2016). This demonstrates the ability of multispectral remote sensing data to monitor soil salinization. Summarizing the previous studies, the use of remote sensing technology for surface salt estimation can be roughly divided into two methods: one is the indirect method based on vegetation index (NDVI, EVI, etc.); the other is the direct method based on salinity index (Allbed and Kumar, 2013). There are also differences in modeling methods using remote sensing to predict surface salinity, such as linear regression models developed based on high correlation between salinity and spectral index, multivariable linear regression models (MLRMs), least squares, and so on. Popularly, remote sensing uses spectral information reflected by different objects to acquire useful earth surface information. Therefore, based on this sense, the use of remote sensing techniques to map the surface salt in soil became possible by using it as a technical specification for soil salinity estimation and monitoring.

Lesch et al. (1995) described the applicability of multiple regression models for salt inversion when the number of samples is small, which may be more suitable for salt marsh wetlands where fieldwork is hard. It seems that it is impractical to use only the remote sensing spectral band to build models due to data redundancy between the original bands. Therefore, many successful cases with more descriptive model had added many auxiliary variables in the process of developing the salt prediction models. For example, the researcher developed a salt prediction model using topographic factors as auxiliary variables in areas where the salt distribution was significantly affected by topography (Yahiaoui et al., 2015; Song et al., 2016; Taghizadeh-Mehrjardi et al., 2016). Scudiero et al. (2015) successfully developed soil salinity prediction models by using the CRSI salinity index and auxiliary variables (soil type, meteorological data and crop type factor) in agricultural land in the western San Joaquin Valley, California, USA. Soil salinity is affected by many factors such as soil moisture, organic matter content, soil texture and surface roughness. Soil surface moisture has an important influence on the spatial distribution of surface salinity. However, there are very few scholars to model soil moisture information as auxiliary variables in previous studies. For this reason, we cannot rule out the influence of surface moisture on the spatial distribution of salt.

In this paper, MLRM using a new auxiliary variable, the Tasseled Cap Transformation wetness band (TCTW), were developed to predict the spatial distribution of salt in the dry lake of the Qehan lake. The applicability of wetness band in predicting surface salt modeling was evaluated to obtain the best model. The possible reasons for the spatial distribution of salt in the dry lake bed were analyzed. The effects of soil moisture and temperature on the spatial distribution of salt were explored.

2. Materials and methods

2.1. Study area

The Qehan Lake (N43° 52'–N43° 58', E114° 46'–E115° 02') is located in Inner Mongolia, China (Fig. 1). The altitude of study area is 900–1500 m above sea level with the Abaga Lava Platform to the north and the Otindag Sandy Land to the south. The lake basin is along the NE–SW direction, and the terrain is high in east and low in west.

The Qehan Lake with an area of 109.3 km² is divided by artificial dam into East and West lakes. East Lake is a freshwater lake with an area of 26.0 km². West Lake with an area of 83.3 km² has dried up to expose the lake bed. These two lakes are relatively closed to rely on surface runoff and atmospheric precipitation for recharge, where the

main water sources are two seasonal rivers, the Gogusty River (into the East Lake) and the Engel River (into the West Lake). The basin area is about 1.4×10^4 km².

The climate is the temperate semi-arid continental monsoon. The southeast monsoon from the sea prevails in the summer to bring plentiful rainfall. In the winter, it is cold, dry and windy, mainly affected by the Siberian-Mongolian high pressure. Mean annual precipitation ranges from 240 to 360 mm, where about 69.4% comes from the rainy season. Mean annual evaporation is 1977.2 mm, which is 7.1 times of the precipitation. The annual average temperature in the Lake district is about 1.3 °C, and the coldest temperature can even be as low as −42 °C affected by the Mongolian high pressure. Mean annual wind speed is 3.3 m/s, perennially west wind, except northeast wind during June–August.

Affected by high and intensive evaporation, salt accumulates on the surface. Frequently, salt is transported to other areas by wind gusts, which can cause a serious impact on the ecological environment of the lake basin and its surroundings.

2.2. Soil sampling and laboratory experiment

The field soil survey was carried out on September 15, 2017. As shown in Fig. 1, in order to better reflect the salt distribution of the entire Qehan Lake bed, the sampling points are distributive so as to obtain higher representativeness of the entire lake bed. At each sampling point, soil samples were taken at the apexes of the triangle (depth: 5 cm) using a soil auger and mixed, and a total of 35 mixed soil samples were obtained. The latitude and longitude information (Accuracy: ± 5 m) of each sample was recorded using a global positioning system (GPS). Each sample was sealed with a storage bag and shipped back to the laboratory for testing. Subsequently, all samples were air dried in a natural state and put through a 2 mm sieve to remove grit. Soil samples were mixed thoroughly with water (soil:water = 1:5) and kept standing for 24 h in order to dissolve all the ions. Finally, the soil leachate was separated using a centrifuge and Electrical Conductivity (EC) was measured using a conductivity meter.

2.3. Satellite images and data processing

In this study we used Landsat 8 because of its convenient acquisition and moderate spatial resolution (30 m). The image on September 26, 2017 was downloaded as the date is closer to the sampling date so that salt information can be accurately reflected. Data was downloaded from the USGS official website (Roy et al., 2014).

Index calculation and preprocessing of Landsat 8 data was conducted using ENVI5.0 (a software dealing with remote sensing graphics) software. Satellite image processing included radiometric, atmospheric corrections and clip. The atmospheric radiance correction for the data was performed by using the FLAASH module in ENVI. The Band Math function was used to compute the selected spectral salinity indices. In this study, spectral indices with certain universality and applicability were selected from previous studies, as shown in Table 1. The criteria for selecting indices are those that can be calculated based on Landsat 8 OLI and have been successfully applied. Among them, the spectral indices SI1, SI2, SI3, SI, and BI are salinity indices concerning the soil brightness information, which can directly reflect land surface information (Douaoui et al., 2006; Khan et al., 2005; Setia et al., 2013). The Ratio Vegetation Index (RVI) is related to vegetation chlorophyll content and can enhance the radiation difference between vegetation and soil background (Major et al., 1990; Song et al., 2016). The Normalized Difference Vegetation Index (NDVI) is related to vegetation cover but is affected by soil background values (Allbed et al., 2014; Deering Jr et al., 1975; Fan et al., 2015; Fernández-Buces et al., 2006; Lobell et al., 2010). The Enhanced Vegetation Index (EVI) enhances vegetation signals by adding blue bands to correct the effects of soil background and aerosol scattering (Douaoui et al., 2006; Liu and Huete,

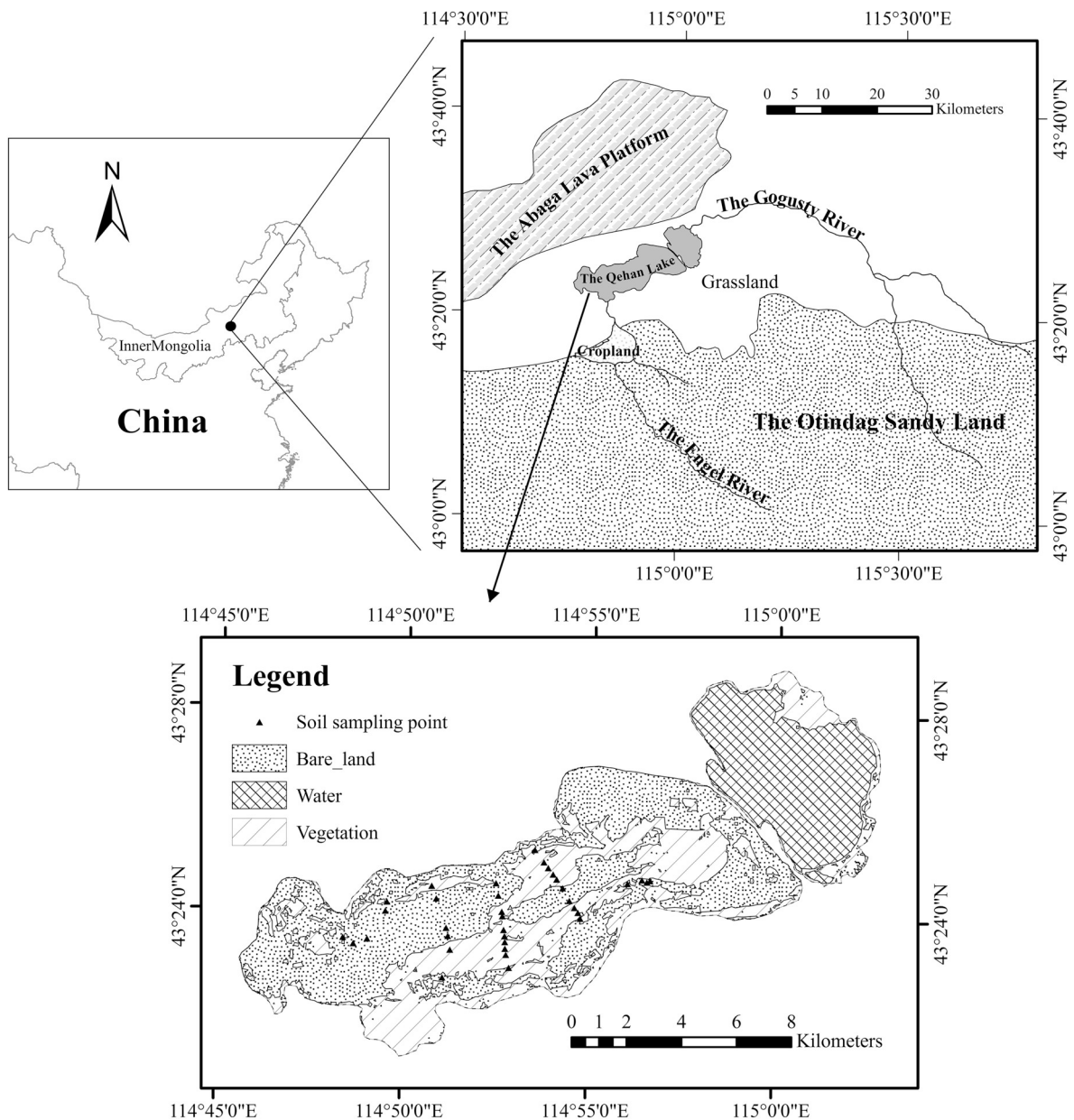


Fig. 1. GPS point location of soil samples and surface features classification at the study area.

Table 1

Alternative vegetation indices and soil salinity indices.

Indices	Equation	References	
1	SI1	$(Green * Red)^{1/2}$	Douaoui et al.,
2	SI2	$(Green^2 + Red^2 + NIR^2)^{1/2}$	2006
3	SI3	$(Green^2 + Red^2)^{1/2}$	
4	SI	$(Blue + Red)^{1/2}$	Khan et al., 2005
5	BI	$(Red^2 + NIR^2)^{1/2}$	
6	SAVI	$(1 + L) * (NIR - Red)/(NIR + Red + L)$	Huete, 1988
7	RVI	NIR/Red	Major et al., 1990
8	EVI	$2.5 * (NIR - Red)/(NIR + 6 * Red - 7.5 * Blue + 1)$	Liu and Huete, 1995
9	NDVI	$(NIR - Red)/(NIR + Red)$	Deering Jr et al., 1975

Note: Number 1–5 are the salinity indices and 5–9 are the vegetation indices. Blue is the blue band, Green is the green band, Red is the red band, NIR is the near-infrared band, L is the empirical constant.

1995; Zhang et al., 2011). The Soil Adjusted Vegetation Index (SAVI) can reduce the impact of the soil background, and the coefficient L is the empirical value of 0.5 in this study (Aboud, 2011; Allbed et al., 2014; Huete, 1988; Koshal, 2010).

Pearson correlation analysis was performed to detect the sensitivity of different remote sensing indices to soil EC. The correlation coefficient can be used as an indicator to reflect the degree of linear correlation between variables. The 0.01 probability level was used to test the significance of the correlation. Pearson correlation analysis of each parameter was performed using SPSS software, the results shown in Table 2.

2.4. Surface temperature inversion

The basis of the split window algorithm is to perform surface temperature inversion with different atmospheric transmission characteristics of two adjacent thermal infrared bands around 11–12 μm (Jimenez-Munoz et al., 2014). The split window algorithm used in this letter is based on the new mathematical structure proposed by Du et al. (2014); Ren et al. (2015) which can reduce the dependence on external

Table 2
Correlation coefficients between measured soil EC values and remote sensing indices and physical variables.

	EC	B1	B2	B3	B4	B5	B6	B7	SI1	SI2	SI3	SI	BI	SAVI	RVI	EVI	NDVI	ST	WB	DEM
EC	1																			
B1	0.756**	1																		
B2	0.753**	0.999**	1																	
B3	0.751**	0.994**	0.996**	1																
B4	0.766**	0.989**	0.992**	0.997**	1															
B5	0.676**	0.691**	0.688**	0.707**	0.688**	1														
B6	0.717**	0.957**	0.962**	0.971**	0.979**	0.635**	1													
B7	0.690**	0.951**	0.957**	0.967**	0.972**	0.646**	0.995**	1												
SI1	0.759**	0.992**	0.995**	0.999**	0.999**	0.698**	0.975**	0.970**	1											
SI2	0.724**	0.750**	0.747**	0.764**	0.749**	0.994**	0.995**	0.702**	0.757**	1										
SI3	0.760**	0.992**	0.995**	0.999**	0.999**	0.697**	0.976**	0.970**	1.000**	0.756**	1									
SI	0.712**	0.985**	0.988**	0.990**	0.986**	0.663**	0.967**	0.965**	0.989**	0.989**	0.926**	1								
BI	0.788**	0.917**	0.917**	0.930**	0.922**	0.913**	0.881**	0.882**	0.927**	0.946**	0.989**	0.896**	1							
SAVI	-0.011	-0.020	-0.019	-0.008	0.008	-0.096	0.027	0.025	-0.001	-0.063	0.001	-0.063	-0.024	1						
RVI	-0.076	0.034	0.033	0.040	0.043	-0.106	0.072	0.074	0.041	-0.078	0.042	0.005	-0.016	0.901**	1					
EVI	-0.009	-0.042	-0.041	-0.026	-0.008	-0.097	0.009	0.007	-0.018	-0.064	-0.016	-0.084	-0.033	0.991**	0.848**	1				
NDVI	-0.535**	-0.870**	-0.878**	-0.877**	-0.885**	-0.323	-0.893**	-0.884**	-0.882**	-0.391**	-0.882**	-0.919**	-0.656**	0.040	0.064	0.107	1			
ST	0.094	0.476**	0.489**	0.496**	0.506**	-0.129	0.564**	0.552**	0.501**	-0.071	0.502**	0.549**	0.212	0.154	0.318	0.137	-0.778**	1		
WB	-0.568**	-0.843**	-0.851**	-0.860**	-0.878**	-0.394	-0.949**	-0.948**	-0.869**	-0.460**	-0.871**	-0.873**	-0.696**	-0.083	-0.137	-0.063	0.902**	-0.688**	1	
DEM	0.111	0.141	0.139	0.146	0.143	0.198	0.207	0.215	0.145	0.179	0.144	0.178	0.169	-0.026	0.003	-0.023	-0.139	0.033	-0.221	1

* Significant at the 0.05 probability level.

** Significant at the 0.01 probability level.

atmospheric conditions and estimated water vapor from thermal infrared image data, with the accuracy of inversion better than 1 °C.

2.5. The Tasseled Cap Transformation

It is accepted that the wetness band obtained from the Tasseled Cap Transformation (TCT) can reflect the soil moisture information of the entire lake bed. For the first time, it was proposed by [Kauth and Thomas \(1976\)](#) to contain the soil moisture information in the TCTW. And, in [Musick and Pelletier \(1988\)](#), it was found that the increase in wetness with gravimetric water content was nearly linear for each soil ($r = 0.93\text{--}0.99$). This result was supported by [Huang et al. \(2002\)](#), [Baig et al. \(2014\)](#), and [Li et al. \(2016\)](#). The TCT can transform multi-dimensional spectral data into bands related to brightness, greenness and wetness with minimal loss of information. This study followed [Baig et al. \(2014\)](#) to task TCT-tool for Landsat 8 in ENVI.

2.6. Multivariable linear regression models and validation

The advantages of a MLRM have been highlighted with aspect to its reduction in the number of samples and multiple prediction functions ([Lesch et al., 1995](#)). MLRMs were constructed using different spectral indices along with the fixed independent variable TCTW.

This work used Origin 9.2 software to build MLRMs and calculate the determination coefficient (R^2), the adjusted coefficient of determination (R_{adj}^2), and the root mean square error (RMSE) to assess the effectiveness of the models.

3. Results and analysis

3.1. Spectral response of sample soils

As shown in [Fig. 2](#), there were significant differences in the spectral reflectance extracted using the central wavelength of different salinity soils in the visible and near infrared bands. In visible and NIR spectral range, slightly saline soils have lower spectral reflectance compared to strongly saline soils. As the center wavelength becomes wider, the spectral reflectance of the soil increases. In the visible range, the spectral reflectance range of the micro saline soil was 9.56%–17.38%, the spectral reflectance range of the medium saline soil was 18.34%–28.05%, and the spectral reflectance range of the strong saline soil was 27.5%–41.71%. The range of spectral reflectance of different salinity soils was irrelevant, which was the reason for using remote sensing to distinguish different salinity soils.

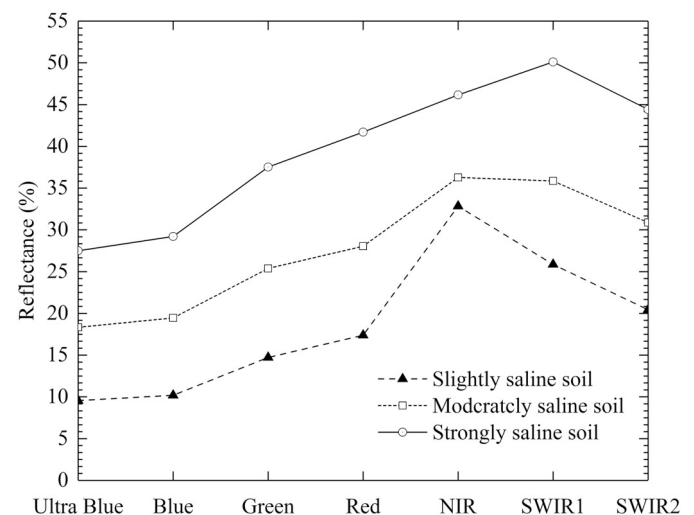


Fig. 2. Spectral reflectance of different soil salinities at the study area.

3.2. Correlation between measured soil EC with remote sensing indices and physical factors

It can be seen from Table 2 that the correlation between measured soil EC and salinity indices is stronger than that with vegetation index. There were strong correlations between measured soil EC and brightness index (BI), and salinity index (SI), which were the basis for multivariable regression modeling. The normalized vegetation index NDVI was moderately correlated, which may be the reason for the low accuracy of model. However, there was no significant correlation with other vegetation indices EVI, RVI, and SAVI. There was no significant correlation between the measured soil EC and the DEM data at the sampling points, the correlation coefficient was only 0.111. However, there was a moderate correlation between the measured EC and soil surface water content, with a correlation coefficient of -0.568 , significant at < 0.01 . The correlation between soil EC and surface temperature information was not significant, and the correlation coefficient was 0.094 , which was the reason that the surface temperature wasn't used as an auxiliary variable.

3.3. Multivariable linear regression models

The accuracy of the multiple linear regression models for each spectral index and the auxiliary variable TCTW were listed in Table 3. As described in the previous section, the accuracy of the MLRM was evaluated by the adjustment coefficient of determination (R_{adj}^2) and the root mean square error (RMSE). The results showed that the MLRM established by BI and wetness band had the best accuracy, with $R_{adj}^2 = 0.598$, $RMSE = 1.640$:

$$EC = 20.13313 * BI - 1.51679 * TCTW - 4.17979 + \varepsilon$$

where, BI is the soil brightness index, TCTW is the Tasseled Cap Transformation wetness band, and ε is the random error component of the model.

However, the MLRM with the vegetation index NDVI was inaccurate, with $R_{adj}^2 = 0.283$, $RMSE = 2.190$. In the inversion consequences of salt on the saline playa at Qehan Lake, the models developed using the salinity index were superior to the vegetation index.

3.4. Soil EC distributions and classification results in the study area

The prediction results of the model developed in this paper were classified with reference to the predecessors' common classification scheme (Abrol et al., 1988):

(1) $0 \text{ dS/m} < EC \leq 2 \text{ dS/m}$ is non-saline soil; (2) $2 \text{ dS/m} < EC \leq 4 \text{ dS/m}$ is slightly saline soil; (3) $4 \text{ dS/m} < EC \leq 8 \text{ dS/m}$ is moderately saline soil; (4) $8 \text{ dS/m} < EC \leq 16 \text{ dS/m}$ is strongly saline soil.

The salt inversion results were discussed in combination with the results of the surface coverage type using the maximum likelihood method for supervised classification. The classification results are shown in Fig. 1. The overall accuracy of the classification results is 99.214%, and kappa coefficient is 0.986.

From the predicted spatial distribution of salinity, the saline soil accounted for the main part of the Qehan Lake region (Fig. 3). The water covered 21.79% of the total study area. Among all saline soil

pixels, 12.09% of the area was slightly saline and the moderately saline area accounts for the largest proportion, which was 54.04%. The strongly saline soil in the lake basin accounted for 7.92%. The above results show that, at present, the saline soil phenomenon was a momentous ecological problem in dry lake bed of the Qehan Lake.

The vegetation area (Fig. 1) in land cover map has overlapping areas with non-saline soil and slightly saline soil in the spatial distribution of salt (Fig. 3), probably due to the fact that the vegetation type is the salt-tolerant vegetation (Latin: Suaeda glauca Bunge).

According to the results of spatial distribution of salinity in the dry lake bed, low salt in the middle of the lake bed, high salt around the dry lake bed. Severe salinization areas are mainly distributed in the eastern, western and southern regions along the lakeshore and vegetative belts.

4. Discussions

4.1. Relationship between measured soil EC with spectral reflectance of different salinities and salinity indices

In Fig. 2, the spectral reflectance of different degrees of salinization was significantly different, which was the main reason for using remote sensing to extract surface salinity information. In a single band, the spectral reflectance of the soil increases as the salinity augments. This discovery was corresponding with those of Allbed et al. (2014), Everitt et al. (1988), and Setia et al. (2013) in which the formation of eflorescence and salt crust was related to high spectral reflectance in the visible and near infrared bands. The accumulation of salt crystals on the surface of saline soil directly leads to this high spectral reflectance, namely, the higher the cumulative amount, the stronger the reflectivity. On the other hand, stable soil structure and high soil organic matter content may be the reason for the low spectral reflectance of the slightly saline soil, as supported by Bannari et al. (2008). The surface of saline soil was often accompanied by white and smooth salt crusts, which may be the reason why the salinity indices (SI, SI1, SI2, SI3) and brightness index (BI) had a significant correlation. Meng et al. (2016) also obtained similar results in the salt marsh wetlands at the estuary of the Yellow River.

However, the vegetation index NDVI had a moderate degree of negative correlation with a correlation coefficient equal to -0.535 , significance level of $P < 0.01$. In this study, the correlation between vegetation indices EVI, RVI, SAVI and measured EC were not significant to indicate that vegetation indices in the study area were not as good as other salinity indices. Allbed et al. (2014) also founded that the vegetation index was not sufficient for the assessment of salinity where vegetation coverage was inadequate. This result agrees with the researches by Bouaziz et al. (2011) and Fan et al. (2012), who discovered that vegetation indices (NDVI, SAVI and EVI) were weak correlation with measured EC values due to insufficient vegetation cover, while the correlation between soil salinity index and EC value was stronger. Another case Zhang et al. (2011) indicated that the vegetation index SAVI was only appropriate for evaluating the salinity of slightly saline districts where salt-tolerant vegetation dominates. Domínguezbeisiegel et al. (2016) showed that the surface of the soil in areas with uneven vegetation varied frequently (Including sparsely vegetated areas, densely populated areas and bare areas), resulting in the combination of vegetation and complex spectra under different soil conditions. From

Table 3
The accuracy of modeling using different spectral indices.

Accuracy	SI1	SI2	SI3	SI	BI	SAVI	RVI	EVI	NDVI	Mean	
										Salinity index	Vegetation index
R^2	0.610	0.595	0.613	0.519	0.621	0.326	0.347	0.325	0.325	0.592	0.331
R_{adj}^2	0.585	0.569	0.589	0.489	0.598	0.284	0.306	0.282	0.283	0.566	0.289
RMSE	1.666	1.698	1.658	1.848	1.640	2.189	2.155	2.191	2.190	1.702	2.181

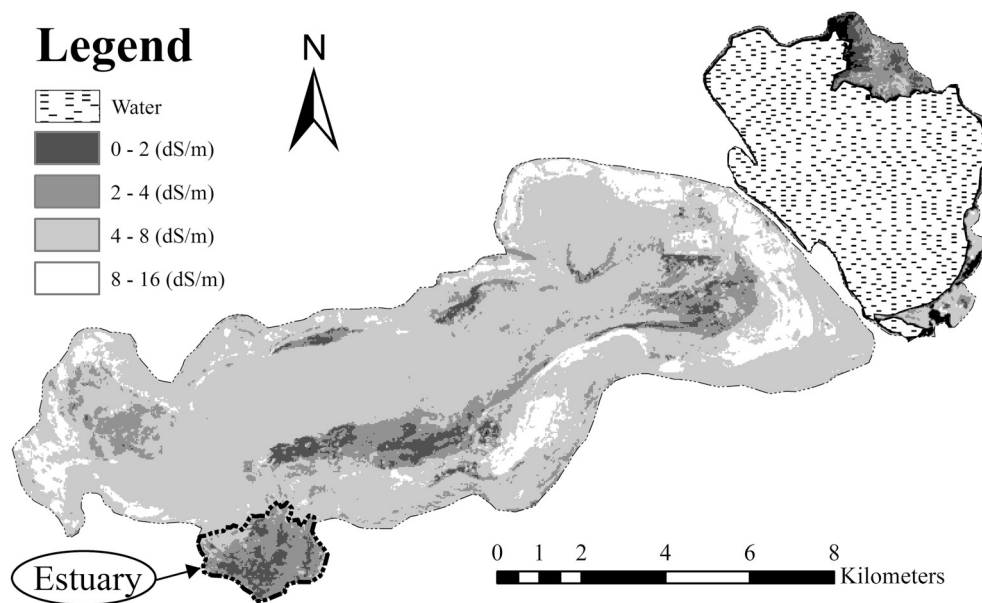


Fig. 3. Spatial distribution of soil salinity across the study area.

the correlation results, the salinity index is superior to the vegetation indices, which may be affected by surface vegetation cover. Vegetation indices may be more suitable for the area is inundated with vegetation. However, in this study area, there is extensive bare land and concentrated vegetation distribution.

In summary, this study studies have shown that both vegetation index and salinity index can be successfully used to evaluate soil salinity, but factors such as environmental conditions, vegetation coverage and density limit the performance of these indices. It seems that there is such a conclusion that if the area of vegetation in the study area is larger than that of bare soil, the vegetation index can be used to evaluate the soil salinity. On the contrary, the soil salinity index is more advantageous if the bare soil area is larger.

4.2. Applicability of the multivariable linear regression models

In this study, the model developed revealed that the prediction of soil salinity was better than the 0.405 determination coefficient (R^2) obtained from the multivariable linear regression technique using MODIS data reported by Bouaziz et al. (2011). And the accuracy was higher than the MLRM established by Yahiaoui et al. (2015) using topographic data (DEM) as an auxiliary variable with R_{adj}^2 of 0.4558 and RMSE of 4.21 dS/m.

The RMSE (also known as the standard error) used to estimate the accuracy of the model is used to measure the deviation between the observed value and the true value. The results showed that the RMSE of the MLRM established using BI and wetness bands was about 1.640 dS/m. The empirical relationship between the measured EC values and the predicted EC values showed that the predicted EC values were too high or too low. In Fig. 4, the predicted soil EC values ranging from 2 to 8 dS/m were higher than the measured soil EC values. However, for predicted soil EC values higher than 8 dS/m, the measured soil EC values may be higher.

From Table 3, the best MLRM was obtained by using BI and wetness bands as independent variables, and its high precision depends on its good correlation. However, the MLRM established using the vegetation index EVI had the lowest accuracy caused by the low correlation between EVI and measured EC. The accuracy of the models established using the salinity indices associated with soil background information was higher than the vegetation indices, which may be related to the distribution of surface cover types. Vegetation indices may have better

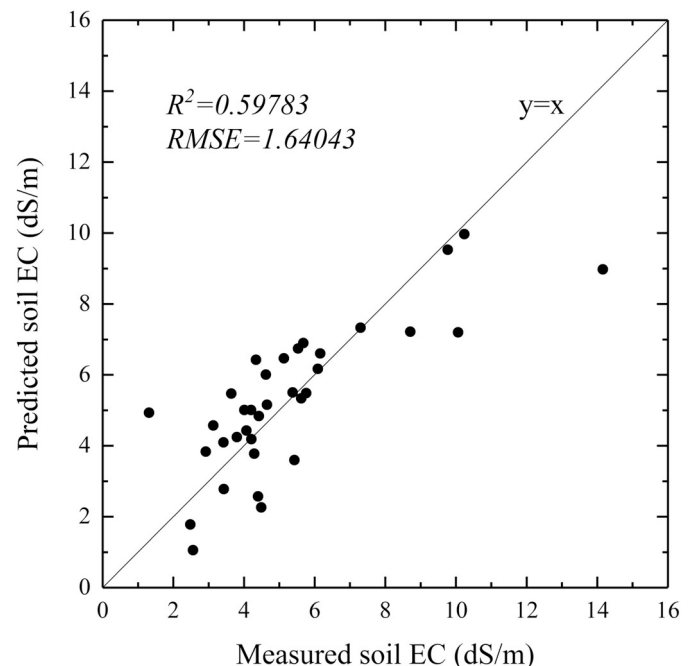


Fig. 4. Scatter plots of measured soil EC and predicted soil EC.

applicability in environments where vegetation and salts are doped-together.

4.3. The reason of soil EC spatial distribution

To the north of the Qehan Lake is the Abaga Lava Platform, which is rich in acidic volcanic lava, acidic pyroclastic rocks, volcanoclastic sedimentary rocks, sandstone, sandy mudstone, glutenite, metamorphic mudstone and other erodible rocks (Fig. 1). It has long been affected by the erosion of the rain and the excessive grazing, resulting in serious soil erosion. A large amount of soluble salt enters the Qehan Lake with running water. To the south of the Qehan Lake is the Otindag Sandy Land, which is composed of aeolian sand and aeolian soil. The soluble salt flows into the lake through the erosion of the Engel River. It is well known that the salt in the estuary of the lake is very high, but the salt

inversion results are not high in the estuary of the Engel River, where the mixed pixels contain multiple end-elements. A pixel may contain a variety of spectral information such as a variety of vegetation types, mixed sediment, water and salt. Complex spectral information may be responsible for the reduced spectral reflectance of the salt. Moreover, the estuary is affected by rainfall to form seasonal stagnant water, which is also the reason for the large-scale growth of *Suaeda glauca* Bunge in the dry lake bed.

The causes of the spatial distribution of salinity may be affected by the shallow groundwater level close to the surface (Yechieli and Wood, 2002). Other scholars mapped the spatiotemporal development of soil salinization in the Yellow River Delta by combining remote sensing data with a spatial model to conclude that the increase in salinity of salinized soil in the Yellow River Delta was related to the increase in shallow groundwater level and the Total Dissolved Solids concentration (Fan et al., 2012).

The causes of the spatial distribution of salt in the Qehan Lake may also be affected by the terrain. Brick red sandy mudstone and sandstone are around the dry lake bed and areas higher than the dry lake bed plain. The banded salt distribution may be related to this topography. An easily erodible slope surrounds the lake bed, similar to the miniature piedmonts. Due to insufficient hydrodynamics and water infiltration, salt accumulates at the bottom of miniature piedmonts. It may even be hindered by banded vegetation to halt the runoff of salinity. The spatial resolution of the DEM data is 30 m, while the width of the miniature piedmont from the lake to the shore is < 30 m. The miniature piedmont and flat lake bed may result in no significant correlation between measured soil EC and DEM data (Chernousenko et al., 2017; Taghizadeh-Mehrjardi et al., 2016; Yahiaoui et al., 2015).

4.4. Response of temperature and moisture to the spatial distribution of salinity

Surface temperature and soil water content have a very strong influence on the dissolution of salt in water to affect the spatial distribution of salt horizontally. There were two ways to aggregate salinity in saturated soils (Yechieli and Wood, 2002). First of all, water evaporates from the surface water or wet surface so that the salt crystallizes on the soil surface to form a white salt shell. The second, the rise and fall of temperature will reduce the solubility of some soluble salts in the

water, resulting in salt crystallization and the formation of white salt shells.

In nature, this dynamics process may develop throughout the year and thermodynamic equilibrium may occur during seasonal changes. In such systems, fluid dynamic conditions may be the limiting conditions for achieving thermodynamic equilibrium. Hence, due to hydrodynamic limitations, certain minerals will not be deposited or dissolved even if salt water reaches thermodynamic saturation (Rosen, 1994a; Yechieli and Wood, 2002).

Fig. 5 shows the scatter plots between measured soil EC and surface temperature or wetness band. From the results of the study, soil water and EC have medium correlation, with a correlation coefficient of -0.568 and a significant correlation at a significance level of 0.01 (Table 2). Salt and soil moisture affect each other. For example, hygroscopic salts such as magnesium salts retain some of their moisture. One possible reason is that the soluble salts in the surface water are saturated, resulting in a decrease in the activity of water molecules, thus reducing the evaporation rate (Sanford and Wood, 2001). Driven by the salt concentration, it is also possible that this salt movement was consistent with water movement where water in the low salinity region moves towards to the high salinity region (Hamann et al., 2016).

As a thermodynamic factor, temperature plays an important role in the distribution of salt. Although there was a bad correlation between measured EC and surface temperature inversion with the correlation coefficient of 0.094 (Table 2), temperature had a very important effect on the solubility of salts and its seasonal variation was significant (surface temperature difference was about 75°C). The effects of temperature on salinity during seasonal changes were significant. Precipitation occurs with reversely dissolvable mineral salts such as gypsum, anhydrite, and calcite at elevated summer surface temperatures. Conversely, sodium chloride and magnesium chloride become supersaturated and precipitate when winter surface temperature decreases (Yechieli and Wood, 2002). Therefore, in the future, we may need to use controlled variables based on different salt types to explore the effect of temperature on the aggregation of soil salinity.

Moisture and temperature can affect the aggregate phenomenon of soil. Nield et al. (2016) used Terrestrial Laser Scanning and infrared images (10–3 m; hours) to co-locate measurements of changing in moisture and salinity topography and found that wetness and temperature affect the change in soil surface texture in the short-term

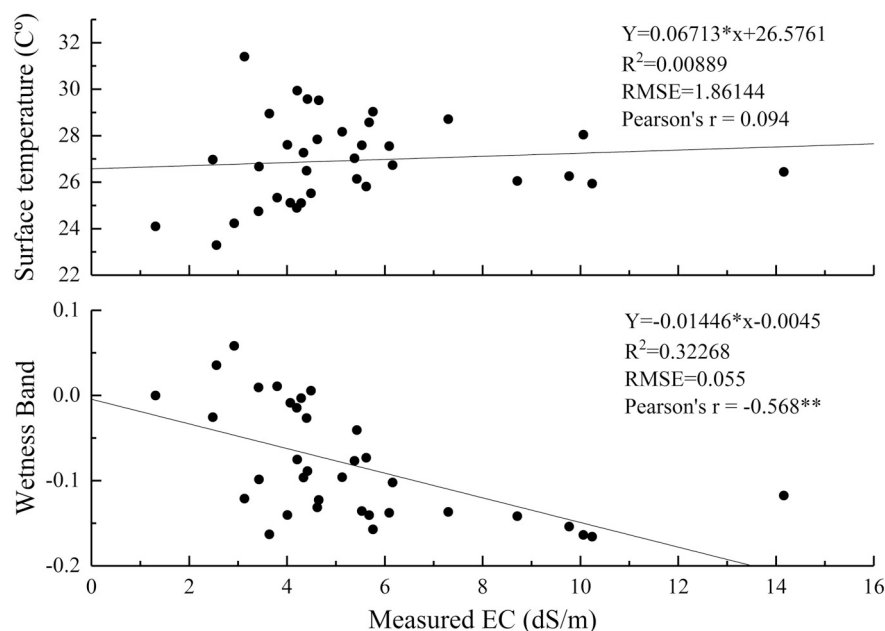


Fig. 5. Scatter plots of measured soil EC and surface temperature or wetness band.

(hours), which may affect the spectral reflectance of the soil. As the results of Romanov and Khvostov (2018), the spectral reflectance of saline decreases with the water content increases, at the same temperature. It is not difficult to find that water affects the salinity distribution on a spatial scale and the temperature influences the salinity variation on a time scale. It is confirmed that the chemical composition of water, temperature, salinity and salt has a great influence on the spectral reflection. Surface soil moisture had an important influence on the spatial distribution of salt, and its correlation was significant, which was also an important reason for our successful modeling. The influence of surface temperature on salt may be biased towards the time scale (such as alternating seasons, large temperature difference between day and night).

5. Conclusion

Based on the Landsat 8 data, this paper used the multivariable regression modeling method to predict the spatial distribution of salt on the saline playa at Qehan Lake. Based on the physical factor (soil moisture) that affects the spatial distribution of salt, we had adopted a new auxiliary variable (the Tasseled Cap Transformation wetness band) for modeling. The results showed that the proposed model had good precision. The MLRM with brightness index (BI) and TCTW as the auxiliary variables had the best precision ($R_{adj}^2 = 0.598$, $RMSE = 1.640$), which demonstrates the potential for modeling using soil moisture information. MLRMs developed based on the vegetation index may be more suitable for vegetation and salt doping environments. In the inversion of the salinity of the dry lake bed in the Qehan Lake, the model developed using the salinity index for soil information is better than using the vegetation index for vegetation information, which may be related to the distribution of surface cover types. Salt distribution may be controlled by flat lake bed and miniature piedmonts. There was a significant correlation between measured soil EC and wetness band, but no correlation with surface temperature. The influence of surface temperature on salt may be biased towards the time scale (such as seasonal changing, large diurnal temperature fluctuations). In this study, the modeling of salt spatial distribution was based on physical significance. The results of this study may be helpful for modeling of geophysical processes in the water-salt migration of the saline playa in the future.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at doi: <https://doi.org/10.1016/j.catena.2019.01.040>. These data include the Google map of the most important areas described in this article.

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